

Chebyshev lattices as unifying framework for point sets used in interpolation and integration

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Overview

1. Generalisation to s-D
2. Chebyshev lattice rules
3. Classification existing rules
4. Search
5. Results
6. Conclusion

1. Generalisation to s-D

1 dimensional:

$$f(x), x \in [-1, 1]$$

- Chebyshev series

$$f(x) = \sum_{h=0}^{\infty} \alpha_h \hat{T}_h(x)$$

- Interpolating approx.

$$f(x) \approx \sum_{h=0}^n a_h \hat{T}_h(x)$$

- Quadrature rule
(Clenshaw-Curtis)

$$\int_{-1}^1 f(x) dx \approx \sum_{h=0}^n a_h I_{[\hat{T}_h]}$$

1. Generalisation to **s**-D

s-dimensional:

$$f(\vec{x}), \vec{x} \in [-1, 1]^s$$

- Chebyshev series

$$f(\vec{x}) = \sum_{\vec{h}} \alpha_{\vec{h}} \hat{T}_{\vec{h}}(\vec{x})$$

- Hyperinterpolation

$$f(\vec{x}) \approx \sum_{\vec{h}, |\vec{h}| \leq n} a_{\vec{h}} \hat{T}_{\vec{h}}(\vec{x})$$

- Cubature rule

$$\int_{[-1, 1]^s} f(\vec{x}) d\vec{x} \approx \sum_{\vec{h}, |\vec{h}| \leq n} a_{\vec{h}} I_{[\hat{T}_{\vec{h}}]}$$

1. Generalisation to **s**-D

HYPERINTERPOLATION

$$f(\vec{x}) \approx \sum_{\vec{h}, |\vec{h}| \leq n} a_{\vec{h}} \hat{T}_{\vec{h}}(\vec{x})$$

Projection into polynomial function space

$$a_{\vec{h}} \approx \int_{[-1,1]^s} f(\vec{x}) \hat{T}_{\vec{h}}(\vec{x}) \omega(\vec{x}) d\vec{x}$$

using cubature rule for **weighted** setting

$$a_{\vec{h}} = \sum_I w_I f(\vec{x}_I) \hat{T}_{\vec{h}}(\vec{x}_I)$$

1. Generalisation to **s**-D

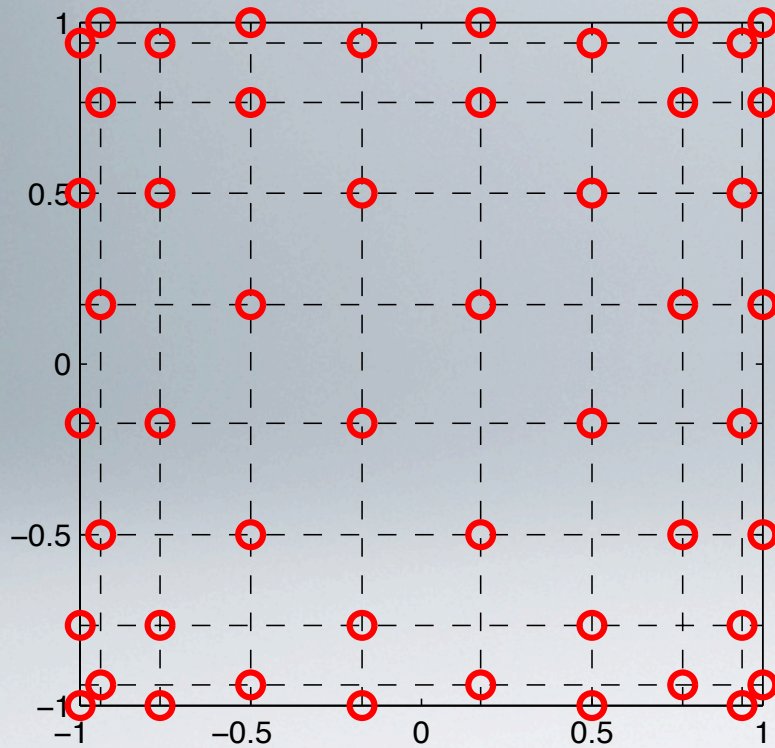
WEIGHTED CUBATURE

$$Q[g] = \sum_I w_I g(\vec{x}_I) \approx \int_{[-1,1]^s} g(\vec{x}) \omega(\vec{x}) d\vec{x}$$

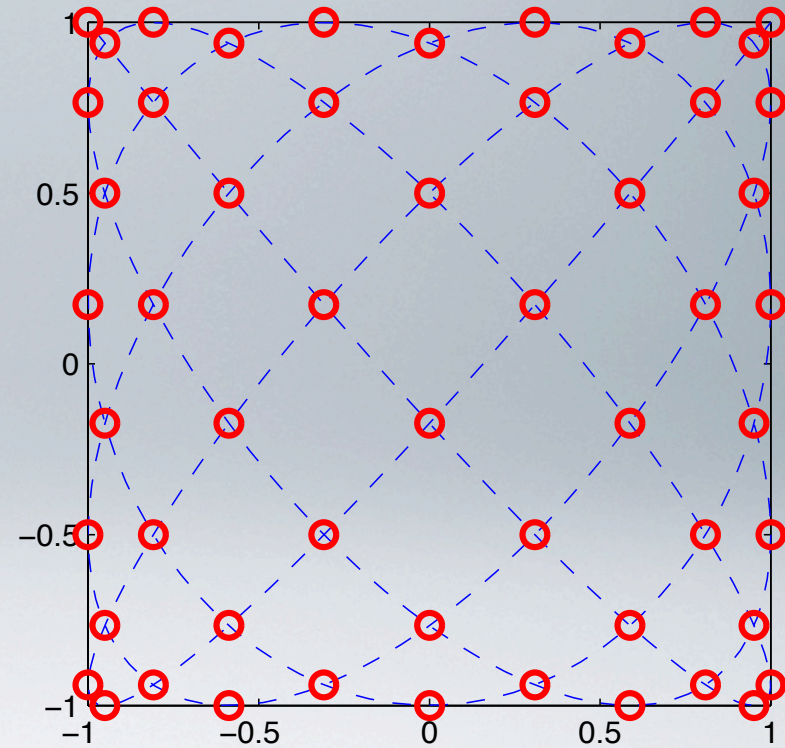
- Several *good* point sets exist
- Known lower bounds on # points
- No clear constructive approach
- Extrema of Chebyshev polynomials

1. Generalisation to s-d

POINT SET EXAMPLES



Morrow-Patterson
(°1978, deg. 17, #50)



Padua
(°2005, deg. 17, #55)

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2. Chebyshev lattice rules

OBJECTIVES

1. Increase number of component values
2. Easy extendible to higher dimensions
3. Compact and uniform representation
4. Enable the use of the FFT
5. Provide a constructive approach

2. Chebyshev lattice rules

Chebyshev Lattice

$$\vec{x}_{\vec{\ell}} = \cos \left(\pi \left(\frac{\ell_1 \vec{z}_1}{d_1} + \dots + \frac{\ell_k \vec{z}_k}{d_k} + \frac{\vec{z}_{\Delta}}{d_{\Delta}} \right) \right)$$

$$\vec{z}_1, \dots, \vec{z}_k, \vec{z}_{\Delta} \in \mathbb{Z}^s \quad d_1, \dots, d_k, d_{\Delta}, \ell_1, \dots, \ell_k \in \mathbb{Z}$$

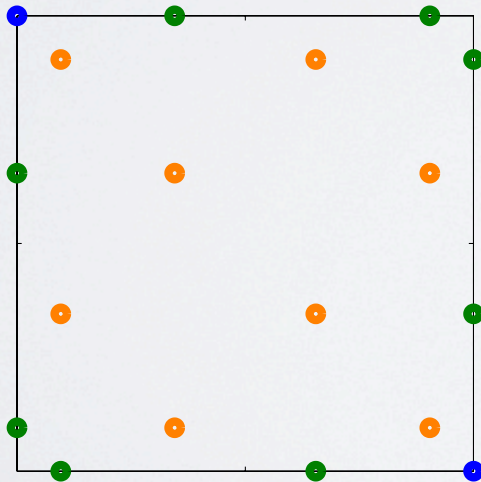
- rank-k integration lattice
- offset vector
- mimic Chebyshev extrema

2. Chebyshev lattice rules

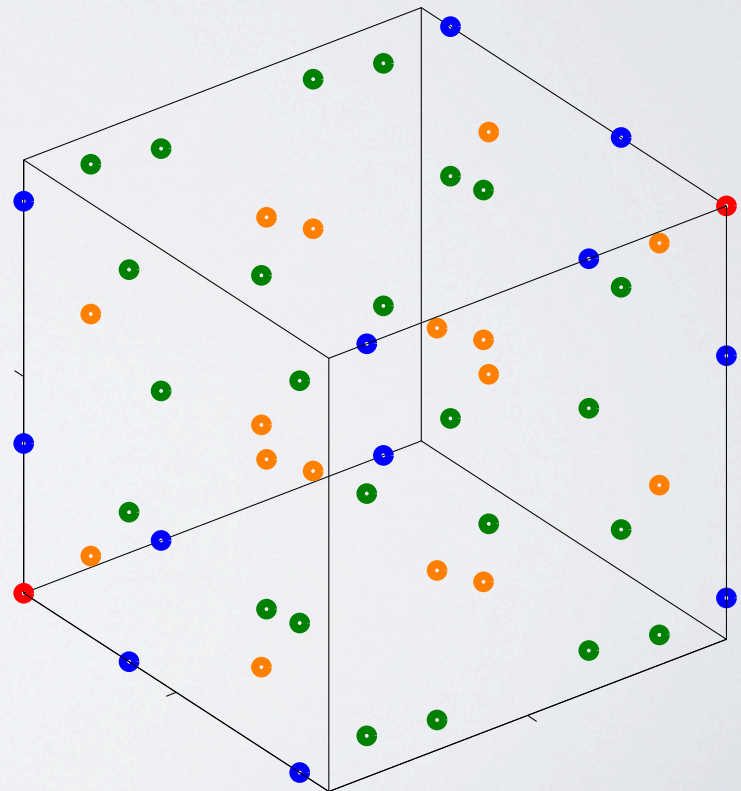
Chebyshev Lattice Rule

$$\vec{x}_{\vec{\ell}} = \cos \left(\pi \left(\frac{\ell_1 \vec{z}_1}{d_1} + \dots + \frac{\ell_k \vec{z}_k}{d_k} + \frac{\vec{z}_{\Delta}}{d_{\Delta}} \right) \right)$$

$$w_{\vec{\ell}} = \text{cte} \left(\frac{1}{2} \right)^{\#_r(|x_{\vec{\ell},r}|=1)}$$



cte
cte/2
cte/4
cte/8



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3. Classification existing rules

Clenshaw-Curtis (1960)

Morrow-Patterson (1978)

$n=11$, fully symmetric (1988)

Minimal D4-invariant (1989)

Blending, Godzina (1994)

Padua (2005)

Xu (2009)

Padua-like (-)

3. Classification existing rules

	k=s (full rank)	k=s-1
s=1	Clenshaw-Curtis (1960)	—
s=2	Morrow-Patterson (1978) n=11, fully symmetric (1988) Minimal D4-invariant (1989)	Padua (2005)
s=3	Blending, Godzina (1994) <i>Xu (2009)</i>	<i>Padua-like (-)</i>
s	Blending, Godzina (1994)	<i>Padua-like (-)</i>

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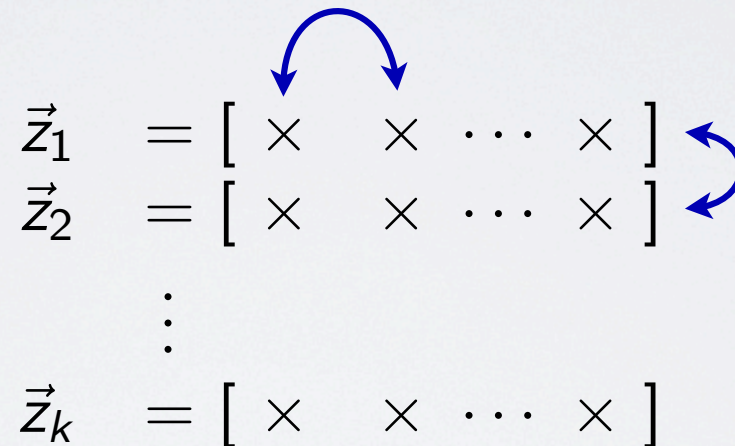
4. Search SETUP

- In 2, 3, 4 and 5-D, not limited to rank-1
- Most basic search algorithm:
 - ➔ for each d
 - ➔ for each $\{\vec{z}_1, \dots, \vec{z}_k\}$
 - create the point set
 - verify its degree
 - store rule if better
- Rank and dimension as parameters

4. Search

SEARCH SPACE REDUCTION

- Size search space: $(d + 1)^{ks}$
- Optimisation: exploit symmetries



The diagram shows a list of vectors $\vec{z}_1, \vec{z}_2, \dots, \vec{z}_k$. Each vector is represented as a row in a matrix, with elements being 'x' or '...' (ellipsis). Blue arrows indicate symmetries: a curved arrow connects the first 'x' of \vec{z}_1 to the second 'x' of \vec{z}_1 , and another curved arrow connects the first 'x' of \vec{z}_2 to the second 'x' of \vec{z}_2 . Additionally, a curved arrow connects the first 'x' of \vec{z}_1 to the first 'x' of \vec{z}_2 , and another curved arrow connects the second 'x' of \vec{z}_1 to the second 'x' of \vec{z}_2 .

$$\begin{array}{l} \vec{z}_1 = [\times \quad \times \quad \cdots \quad \times] \\ \vec{z}_2 = [\times \quad \times \quad \cdots \quad \times] \\ \vdots \\ \vec{z}_k = [\times \quad \times \quad \cdots \quad \times] \end{array}$$

- How to generate these vectors?

4. Search

SEARCH SPACE GENERATION

- Parametric representation

- i.e. $s=3$, rank-1:

$[A,A,A]$
 $[A,A,B]$
 $[A,B,B]$
 $[A,B,C]$

for $A, B, C = 0, \dots, d$
 $A < B < C$

- i.e. $s=2$, rank-2:

$[A,A]$ $[A,B]$
 $[A,B]$ $[A,C]$
 $[A,B]$ $[B,A]$
 $[A,B]$ $[C,A]$

...

for $A, B, C, D = 0, \dots, d$
 $A < B < C < D$

- Parameters through (almost) loopless algorithm

4. Search

POINT SET CREATION

- Problem: duplicates
- Red-black tree comparison is bottleneck ...

$$\vec{x}_\ell = \cos \left(\frac{\pi}{d} \ell \vec{z} \right)$$

integer

- avoid floating point

- **reduce** integer parts to $[0, d]$: $\vec{y}_\ell = \text{minmod}(\ell \vec{z})$

- exploit large integer length

- composite scalar: $y_\ell = \sum_{r=1}^s (d+1)^{r-1} \text{minmod}(\ell z_r)$

4. Search

DEGREE VERIFICATION

- Test inner cubature rule for all $\hat{T}_{\vec{h}} \quad (|\vec{h}| \leq n)$
evaluation is bottleneck
 - cache intermediate results
 - trade off: storage vs. computations
 - change order of coefficients \vec{h}
 - maximise intermediate cache “hits”
 - (almost) loopless algorithm

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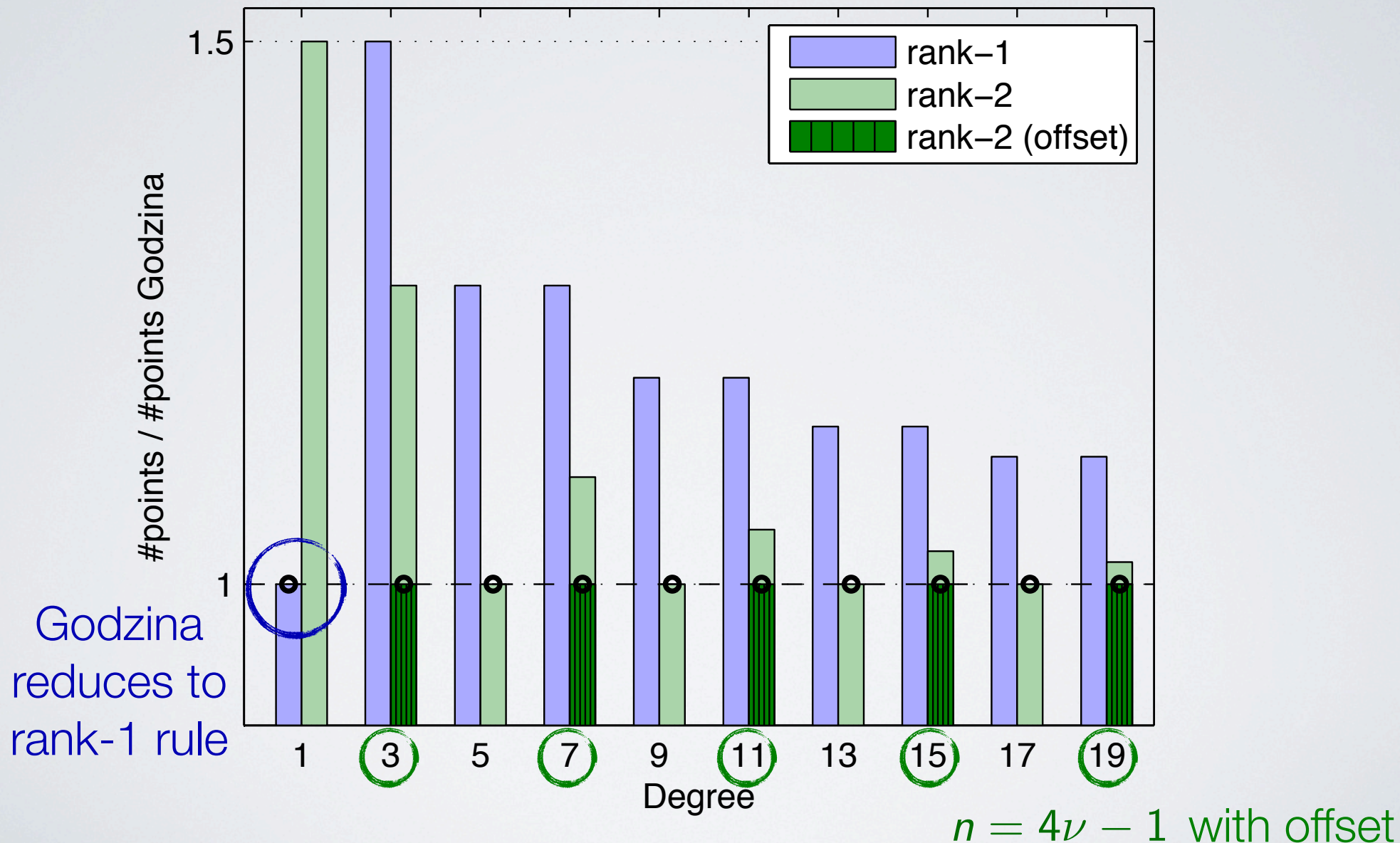
5. Results

GENERAL REMARKS

- Distinct component values still small
 - grid-like structure decreases #points
- No point sets better than already known before
 - Godzina best
- Observations:
 - high rank consistently better than low rank
 - offset vectors often reduce # points

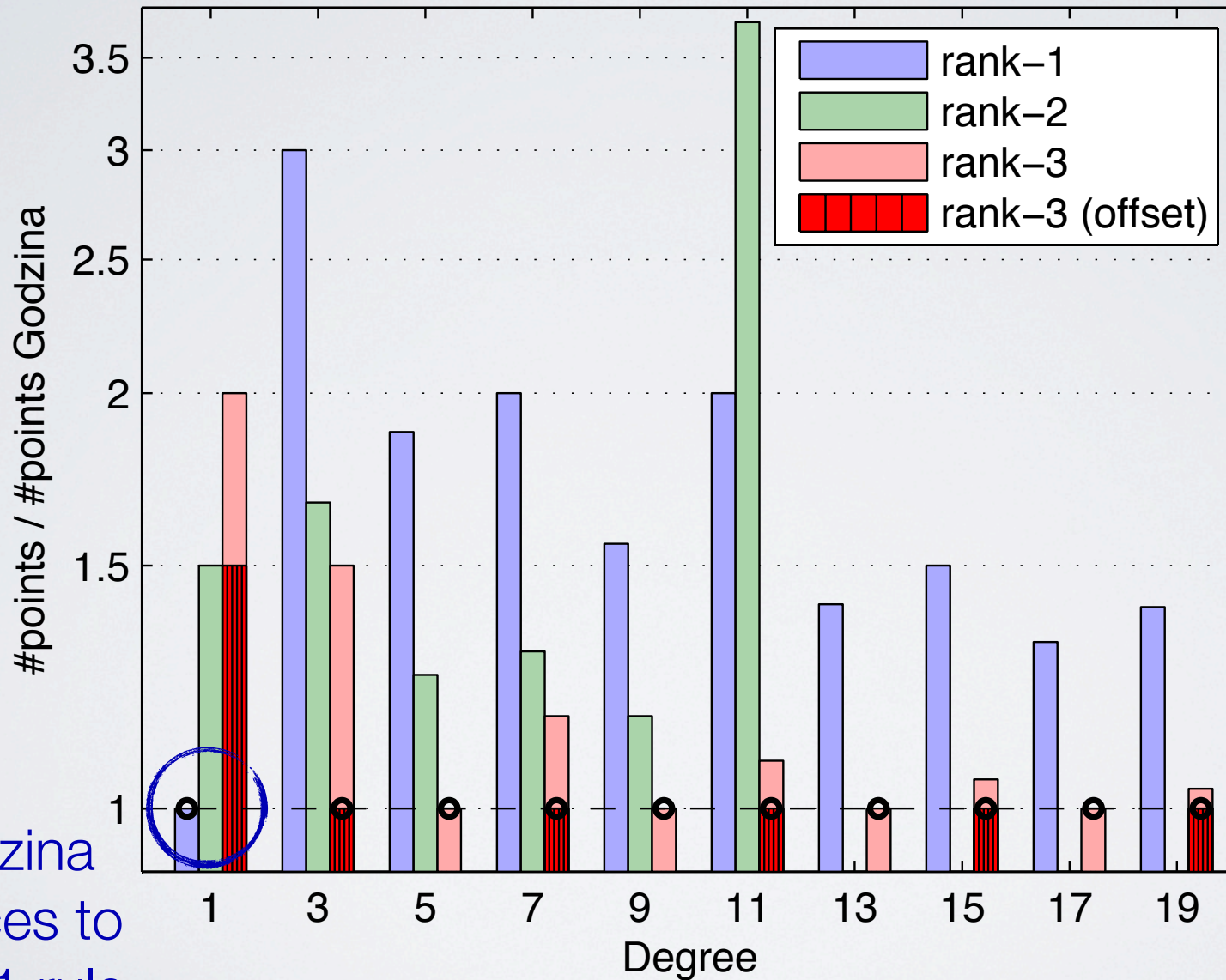
5. Results

2-DIMENSIONS



5. Results

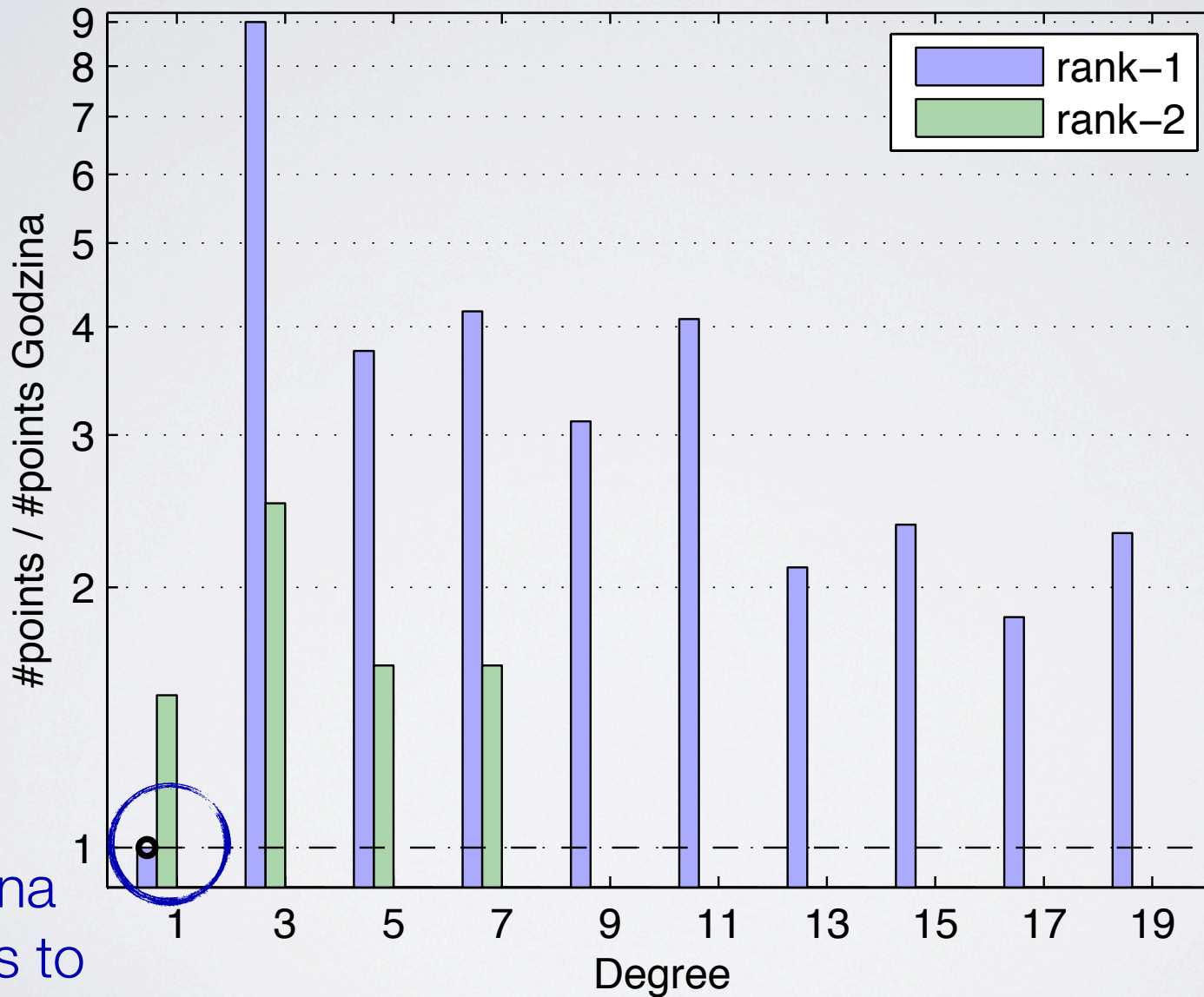
3-DIMENSIONS



Godzina
reduces to
rank-1 rule

5. Results

4-DIMENSIONS (INCOMPLETE)



Godzina
reduces to
rank-1 rule

6. Conclusion

- Multivariate extension of Clenshaw-Curtis
 - Chebyshev lattices as general framework
 - Uniform description for known point sets
 - High rank computational search
 - Godzina blending formulae still best
 - Rank-1 rules interesting special case
 - Cubature rules suited for oscillatory functions
- Future work